

UNIVERSITY OF TECHNOLOGY SYDNEY
Faculty of Engineering and Information Technology

**Mobile Edge Computing for Future
Internet-of-Things**

by

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Certificate of Authorship/Originality

I, Chenshan Ren, declare that this thesis, is submitted in fulfilment of the requirements for the award of doctor of philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney. This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree except as fully acknowledged within the text. This thesis is the result of a research candidature jointly delivered with Beijing University of Posts and Telecommunications as part of a Collaborative Doctoral Research Degree. This research is supported by the Australian Government Research Training Program.

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ABSTRACT

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Integrating sensors, the Internet, and wireless systems, Internet-of-Things (IoT) provides a new paradigm of ubiquitous connectivity and pervasive intelligence. The key enabling technology underlying IoT is mobile edge computing (MEC), which is anticipated to realize and reap the promising benefits of IoT applications by placing various cloud resources, such as computing and storage resources closer to smart devices and objects. Challenges of designing efficient and scalable MEC platforms for future IoT arise from the physical limitations of computing and battery resources of IoT devices, heterogeneity of computing and wireless communication capabilities of IoT networks, large volume of data arrivals and massive number connections, and large-scale data storage and delivery across the edge network. To address these challenges, this thesis proposes four efficient and scalable task offloading and cooperative caching approaches are proposed.

Firstly, for the multi-user single-cell MEC scenario, the base station (BS) can only have outdated knowledge of IoT device channel conditions due to the time-varying nature of practical wireless channels. To this end, a hybrid learning approach is proposed to optimize the real-time local processing and predictive computation offloading decisions in a distributed manner.

Secondly, for the multi-user multi-cell MEC scenario, an energy-efficient resource management approach is developed based on distributed online learning to tackle the heterogeneity of computing and wireless transmission capabilities of edge servers and IoT devices. The proposed approach optimizes the decisions on task offloading, processing, and result delivery between edge servers and IoT devices to minimize

the time-average energy consumption of MEC.

Thirdly, for the computing resource allocation under large-scale network, a distributed online collaborative computing approach is proposed based on Lyapunov optimization for data analysis in IoT application to minimize the time-average energy consumption of network.

Finally, for the storage resource allocation under large-scale network, a distributed IoT data delivery approach based on online learning is proposed for caching application in mobile applications. A new profitable cooperative region is established for every IoT data request admitted at an edge server, to avoid invalid request dispatching.

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List of Publications

Journal Papers

- J-1 . C. Ren, X. Lyu, W. Ni, H. Tian, R. P. Liu. “*Distributed Online Learning of Fog Computing under Non-uniform Device Cardinality*” in ***IEEE Internet of Things Journal***, vol. 6, no. 1, pp. 1147-1159, Feb. 2019.
- J-1 . C. Ren, X. Lyu, W. Ni, H. Tian, R. P. Liu. “*Profitable Cooperative Region for Distributed Online Edge Caching*” in ***IEEE Transactions on Communications***, vol. 67, no. 7, pp. 4696-4078, Jul. 2019.
- J-3 . X. Lyu, C. Ren, W. Ni, H. Tian, R. P. Liu, Y. Jay Guo. “*Multi-timescale Decentralized Online Orchestration of Software-Defined Networks*” in ***IEEE Journal on Selected Areas in Communications***, vol. 36, no. 12, pp. 2716-2730, Dec. 2018.
- J-4 . X. Lyu, C. Ren, W. Ni, H. Tian, R. P. Liu. “*Distributed Optimization of Collaborative Regions in Large-Scale Inhomogeneous Fog Computing*” in ***IEEE Journal on Selected Areas in Communications***, vol. 36, no. 3, pp. 574-586, March 2018.
- J-5 . X. Lyu, C. Ren, W. Ni, H. Tian, R. P. Liu, E. Dutkiewicz. “*Optimal Online Data Partitioning for Geo-Distributed Machine Learning in Edge of Wireless Networks*” in ***IEEE Journal on Selected Areas in Communications***, DOI: 10.1109/JSAC.2019.2934002.

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Abbreviation

Internet of Things - IoT

Mobile Edge Computing - MEC

Mobile Edge Computation Offloading - MECO

Quality of service - QoS

Small Cell Management entity - SCM

Mobile Micro Clouds - MMC

Fast Moving Personal Cloud - MobiScud

Follow Me Cloud - FMC

Radio Access Network - RAN

Online Convex Optimization- OCO

Stochastic Gradient Descent- SGD

Mixed integer programming - MIP

Dynamic programming- DP

Time-division multiple access - TDMA

Quality of experience - QoE

Base station - BS

Long-term evolution - LTE

Mixed integer non-linear programming - MINLP

KarushKuhnTucker - KKT

Cumulative distribution function - CDF

Integer programming - IP

Linear programming - LP

Independent and identical distributed - i.i.d.

Round robin - RR

Proportional fair - PF

Device-to-Device - D2D

Precision time protocol -PTP

First-in-first-out - FIFO

Left-hand-side - LHS

Right-hand-side - RHS

Neighbor discovery protocol - NDP

Head-of-line - HOL